Applying Artificial Intelligence (AI) Based Signal Coordination and Controls for Optimized Mobility for the Nimitz Highway

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Oak Ridge National Laboratory

Project ID: EEMS090

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2022 Vehicle Technologies Annual Merit Review
June 2022

Overview

Timeline

- Project start date: 01 Feb 2021
- Project end date: 31 Jan 2023
- Percent complete: 60.0%

Budget

- Total project funding: $2M
  - DOE share: $2M
  - Contractor share: 0
- Funding for FY 2021: $257k
- Funding for FY 2022: $1150k
- Funding for FY 2023: $593k

Barriers and Technical Targets

- Barriers addressed
  - Data quality: we applied pre-filtering algorithm to improve the data for the modeling using neural networks
  - Large model parameters: We developed hybrid neural network to reduce model parameters
  - Real-time implementation

Partners

- Interactions/collaborations: University of Hawaii, Econolite Systems, Hawaii DOT
- Project lead: ORNL

1. Relevance

Impact:

- Since traffic systems are dynamic, nonlinear and stochastic, this project will develop AI-based modeling and controls for the first-time on 24/7 real-world implementation.
- Address the effects of future mobility technologies and services on VTO's research portfolio – and thus significantly expend the DOE landscape for real-world implementation of AI for Mobility.
- Use data sources and facilities built via the recent investment from the Hawaii DOT to its busiest arterial for improved traffic system monitoring and operation.

Objective:

- Develop and apply AI based modeling and control for Optimized Mobility for the Nimitz Highway and Ala Moana Boulevard Arterial in Honolulu
- Operate the AI based modeling and control 24/7 as a real-time implementation to see the benefit of advanced signal controls

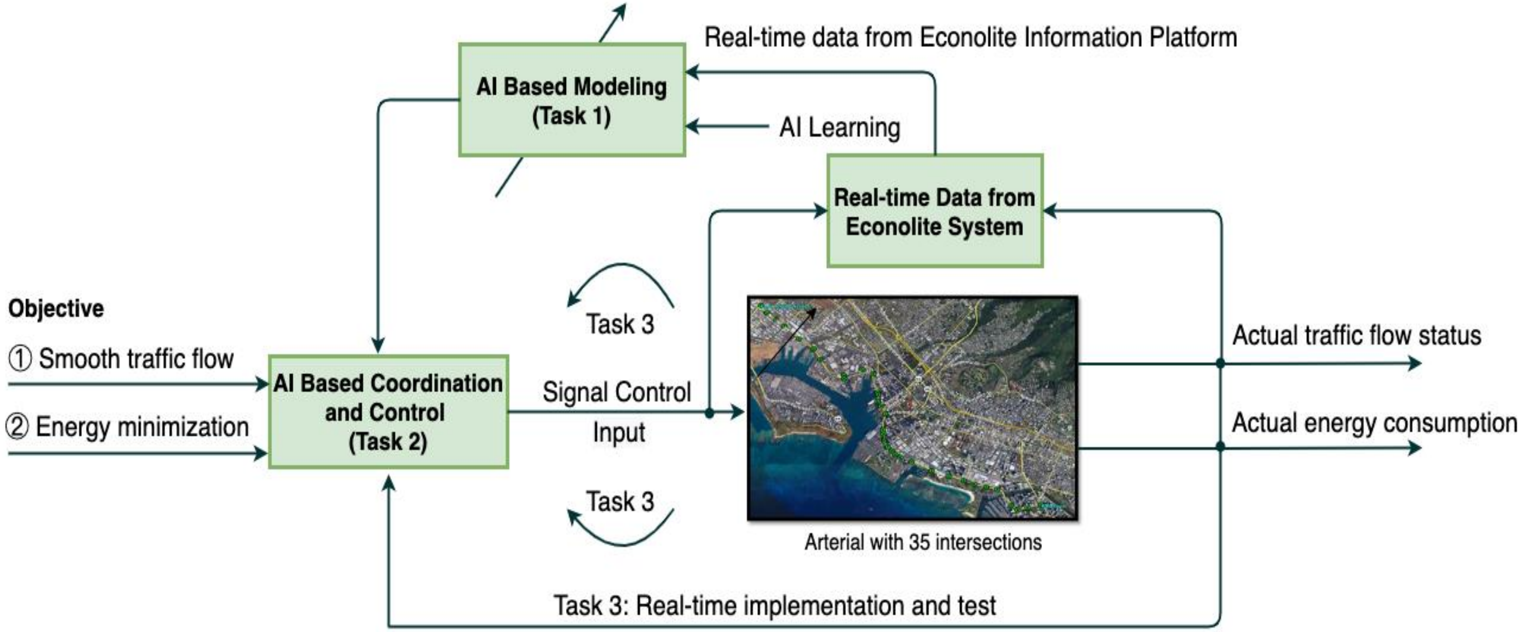


Figure 1. The closed loop system structure and tasks

2. Tasks and Milestones (Project duration on 02/01/2021 - (

Milestone	Description	When	Status
AI-based modeling	Complete AI-based modeling for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu with a <10% modeling error and a 95% confidence interval. .	Month 5	Completed
AI-based control	AI-based control strategy completed with a <5% closed-loop control error, 15% energy savings, and 25% reduced travel delays for simulated scenarios. **Go/no-go: Successful completion of AI-based modeling and control design in month 12**	Month 12	Completed (to further improve energy modeling)
Integrating with the Econolite system	Complete the integration and testing of AI-based modeling and control on the Econolite control system platform together with all the software and hardware interface for real-time implementation.	Month 19	In progress
Real-world testing	Complete the implementation of the AI-based control for the Nimitz Highway and Ala Moana Boulevard arterial in Honolulu with at least 15% energy savings and 25% of travel delay reduction compared with the baseline case of Econolite controls. Submit a paper to a leading transportation journal.	Month 24	In progress

3. What have been achieved

- Competed two milestones (Modeling, VISSIM and Optimal AI-based Control) as planned with

  a) modeling error < 10% at 96% confidence,
  b) control improvement > 30% travel delay reduction, fuel reduction 10% (preliminary result)

- Presented a keynote speech at 2021 Vehicular Conference;

- Received the best paper award at 2021 Vehicular Conference;

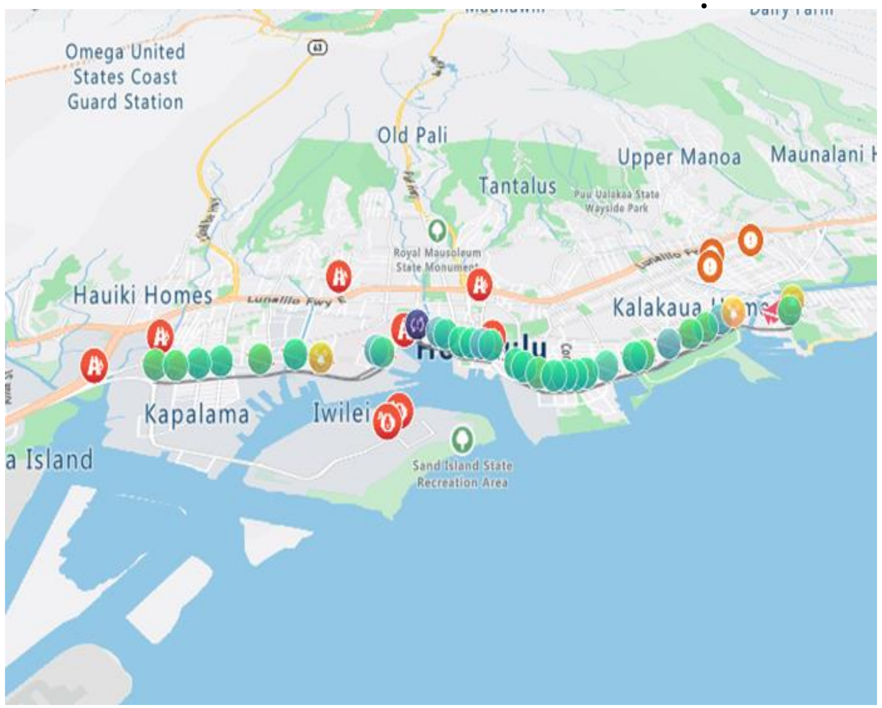
- A poster in TRB in 2022;

- A journal paper titled "Hybrid Neural Network Learning for Multiple Intersections along Signalized Arterials - A Microscopic Simulation vs Real System Effect“ per invited by *International Journal On Advances in Networks and Services*, v 14 n 1&2 2021;

- A journal paper at the prestigious *IEEE Transactions on Intelligent Transportation Systems* (minor revision) titled "Hybrid Recurrent Neural Network Modeling for Traffic Delay Prediction at Signalized Intersections Along an Urban Arterial,"

4. Approach

Table 1. Available data from the new communication and data platform in the following table

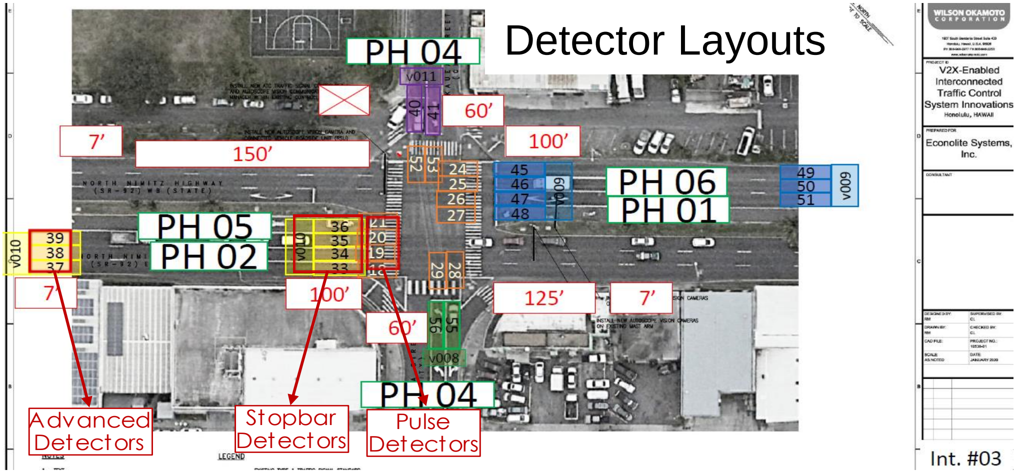


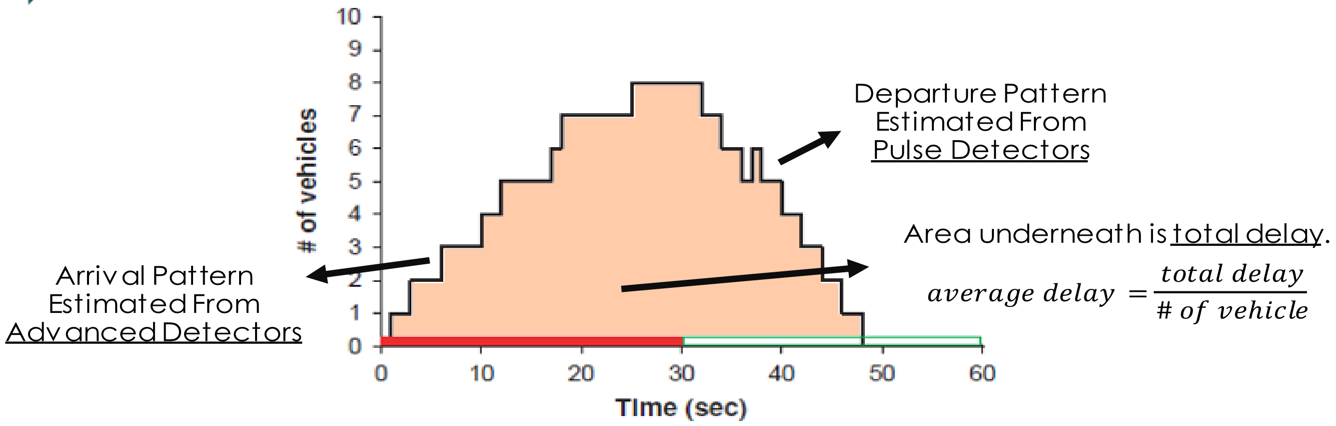
Data 1:	**All the signal control status parameters along arterials**
Data 2:	CCTV-based video detection (volumes, occupancy, queue length, etc.)
Data 3:	Arterial performance measurement (arterial travel time, control delays, number of stops)
Data 4:	V2X communication and customized connected vehicle trajectories
Data 5:	Real-time advanced traveler information system

4.1 Date Collection and Processing

Objective: Obtain High-Resolution Delay Data from Econolite System and Travel Delay Calculation

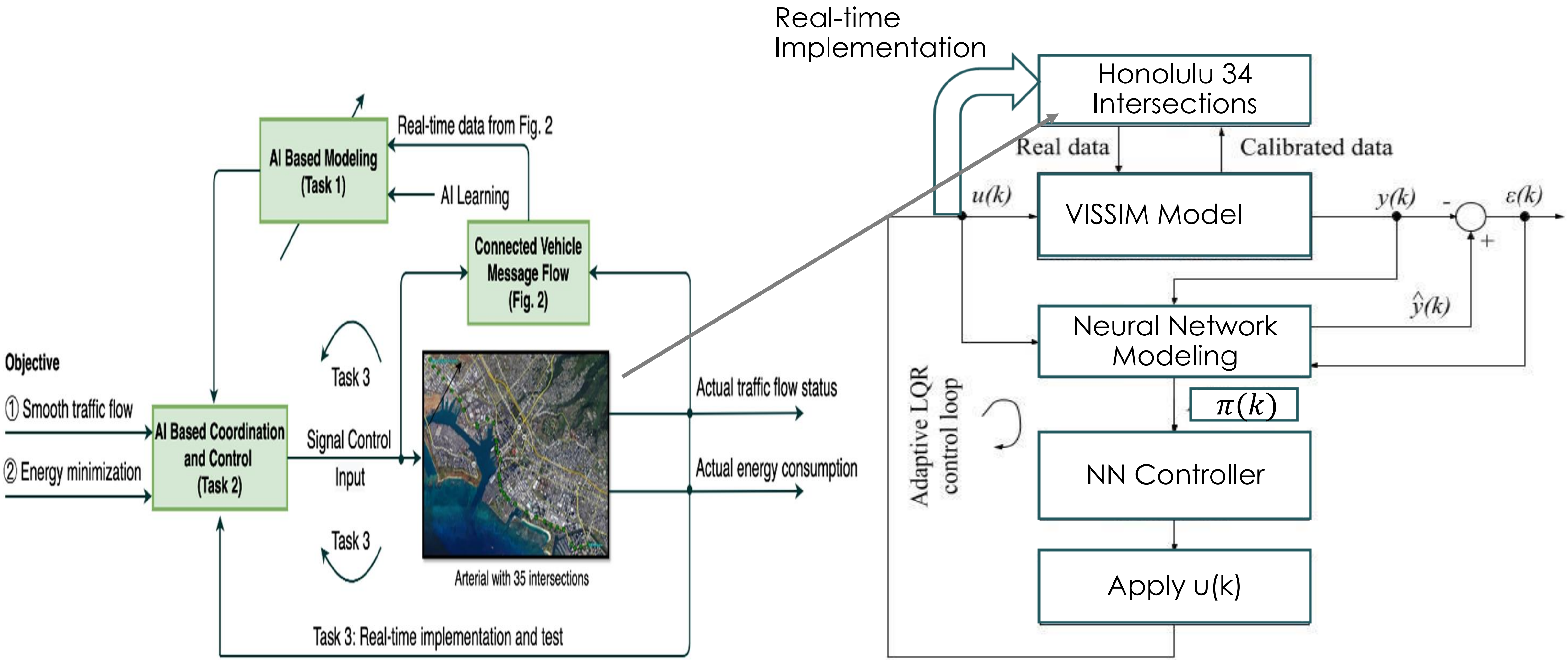
timestamp	Event code	Event Param	
2/1/2021 11:27:30	44	1	
2/1/2021 11:27:31	7	1	
2/1/2021 11:27:31	8	1	
2/1/2021 11:27:31	63	13	
2/1/2021 11:27:33	81	36	
2/1/2021 11:27:33	44	5	
2/1/2021 11:27:33	82	37	Detector on, Detector id 37
2/1/2021 11:27:33	7	5	Green off, phase 5
2/1/2021 11:27:33	8	5	Yellow on, phase 5
2/1/2021 11:27:33	63	15	
2/1/2021 11:27:33	81	37	Detector off, Detector id 37
2/1/2021 11:27:35	10	1	Red clearance on, phase 1
2/1/2021 11:27:35	9	1	
2/1/2021 11:27:35	64	13	
2/1/2021 11:27:35	65	13	
2/1/2021 11:27:36	0	2	
2/1/2021 11:27:36	11	1	Red clearance off, phase 1
2/1/2021 11:27:36	1	2	Green on, phase 2
2/1/2021 11:27:36	2	6	
2/1/2021 11:27:36	12	1	
2/1/2021 11:27:36	21	2	
2/1/2021 11:27:37	10	5	
2/1/2021 11:27:37	9	5	
2/1/2021 11:27:37	64	15	
2/1/2021 11:27:37	65	15	
2/1/2021 11:27:38	0	6	
2/1/2021 11:27:38	11	5	
2/1/2021 11:27:38	1	6	
2/1/2021 11:27:38	12	5	
2/1/2021 11:27:38	21	6	





- All events from advanced, stopbar and pulse detectors are extracted as well as signal timing of all phases.
- Queue length of each phase is estimated to calculate delay.

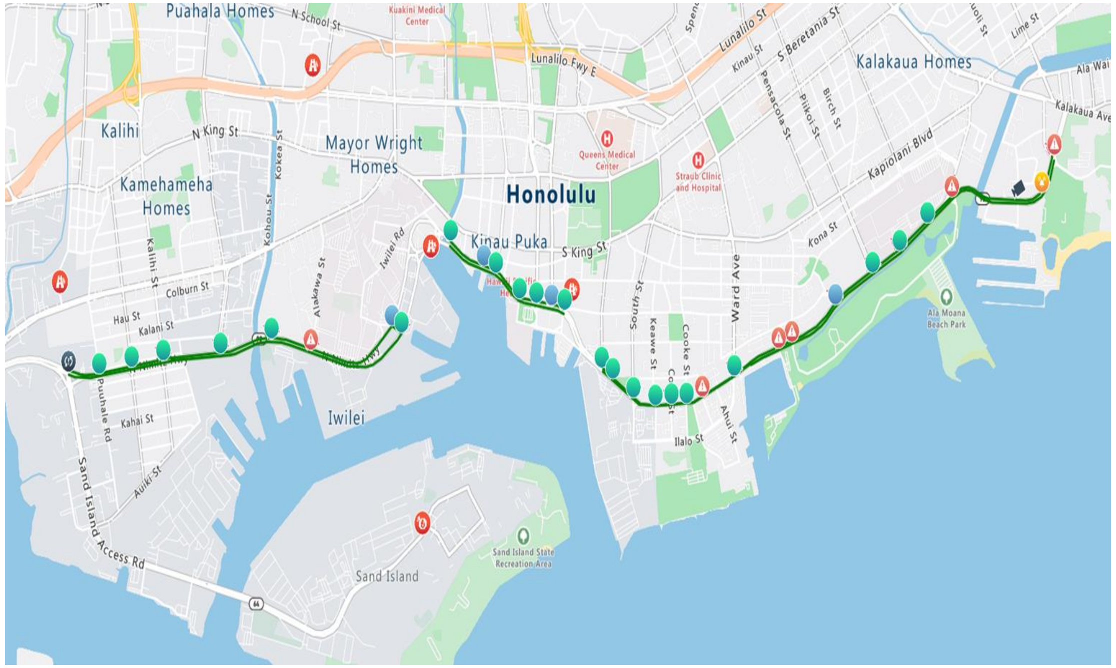
4.2 VISSIM Driven Control Design



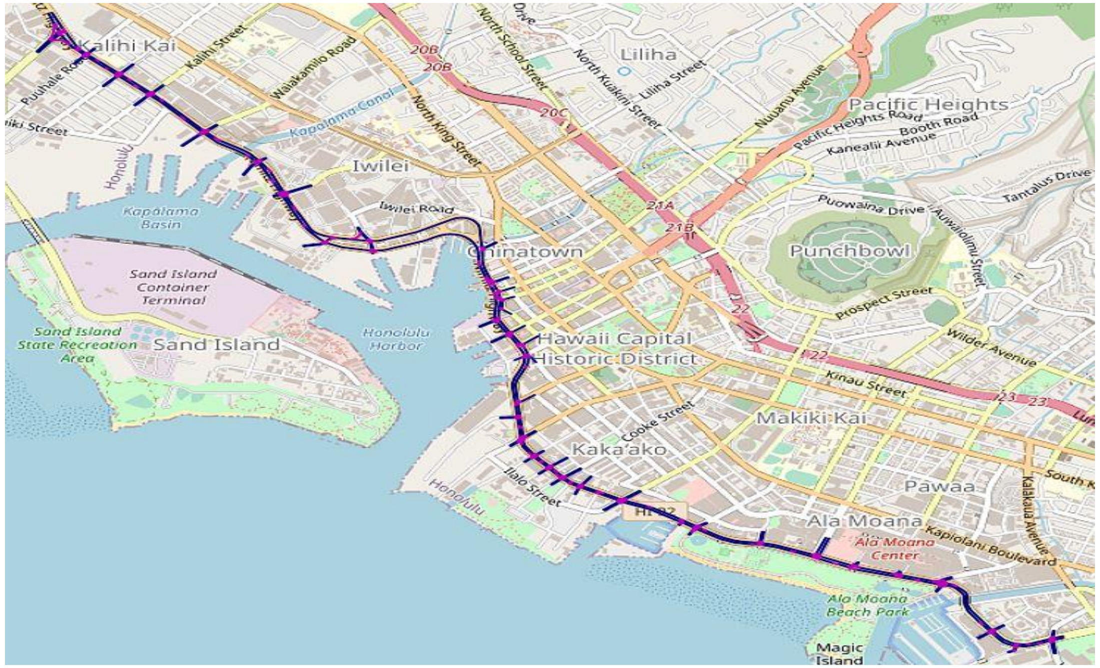
4.2 VISSIM Implementation of Econolite Network

- Adaptive closed loop signal control for corridor #1.

Econolite Network



Vissim Network



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4.3 Hybrid Neural Network (HNN) Model

- **HNN Model**

$$y(k+1) = Ay(k) + Bu(k) + \omega(k) \quad (1)$$

Linear model

where $y(k)$ and $u(k)$ denote average delay per vehicle and green time for multiple intersections at time index k. $\omega(k)$ is noise. {A, B} are the weight matrix. Rewrite (1) to (2):

New feature: traffic volume

$$y(k+1) = \underbrace{\boxed{Ay(k) + Bu(k)}}_{\text{Linear}} + \underbrace{\boxed{f(y(k), u(k-1), v(k))}}_{\text{NN}} \quad (2)$$

HNN

Let NN to approximate $f\big(y(k), u(k-1), v(k)\big)$ by $\hat{f}(y(k), u(k-1), v(k), \pi)$, $v(k)$ denote traffic volume.

This is Achieved by minimizing Eq.(3) using gradient approach.

$$\text{Min } J = \frac{1}{2}(\hat{y}(k+1) - y(k+1))^2 \quad (3)$$

Objective

$$\hat{y}(k+1) = Ay(k) + Bu(k) + \hat{f}(y(k), u(k-1), v(k), \pi) \quad (4)$$

{A, B, π} are parameters to be trained. π groups all NN weights and bias.

4.3 Hybrid NN model – Online Training Using Econolite Data

- Model parameters {A, B, π} are trained simultaneously by (6)-(11):

$$\hat{A}(k+1) = \hat{A}(k) - \lambda_1 \frac{\partial J}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (6)$$

$$\hat{B}(k+1) = \hat{B}(k) - \lambda_2 \frac{\partial J}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (7)$$

$$\hat{\pi}(k+1) = \hat{\pi}(k) - \lambda_3 \frac{\partial J}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (8)$$

Parameter update rules

where λ_1, λ_2, λ_3 are learning rates.

$$\frac{\partial J}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{y}}{\partial A}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\, y(k) \quad (9)$$

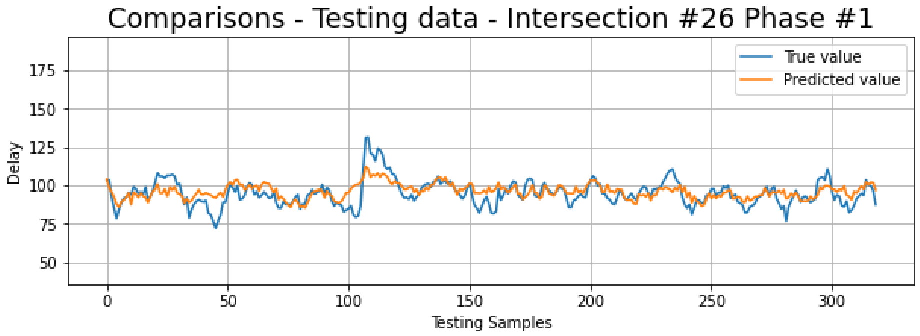
$$\frac{\partial J}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{y}}{\partial B}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\, u(k) \quad (10)$$

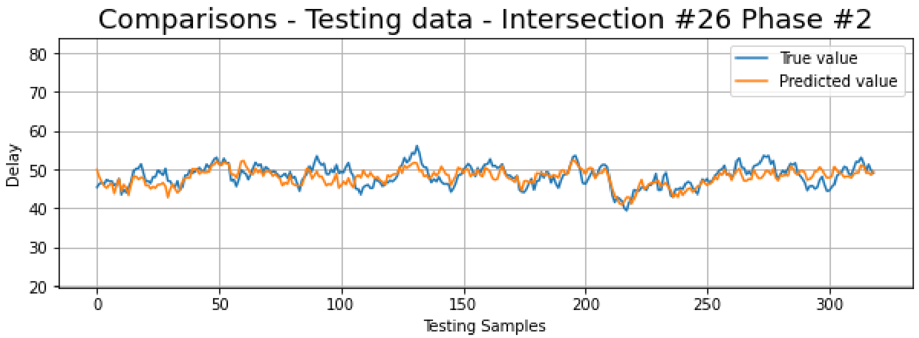
$$\frac{\partial J}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} = (\hat{y}(k+1) - y(k+1))\frac{\partial \hat{f}}{\partial \pi}\Big|_{(\hat{A}(k),\hat{B}(k),\hat{\pi}(k))} \quad (11)$$

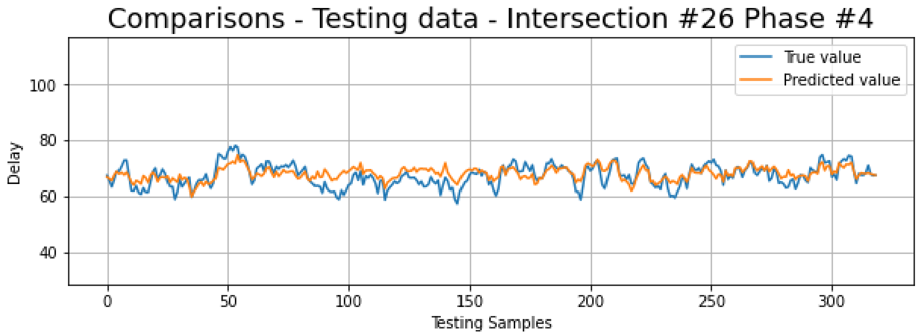
where y(k+1) is the measured data.

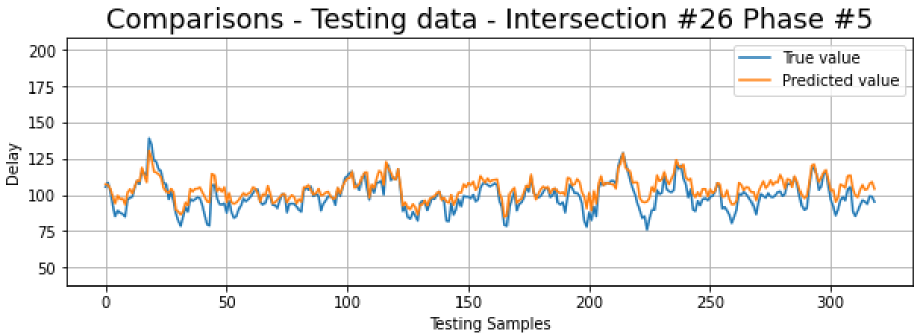
4.3 Experiment Results: Corridor 4

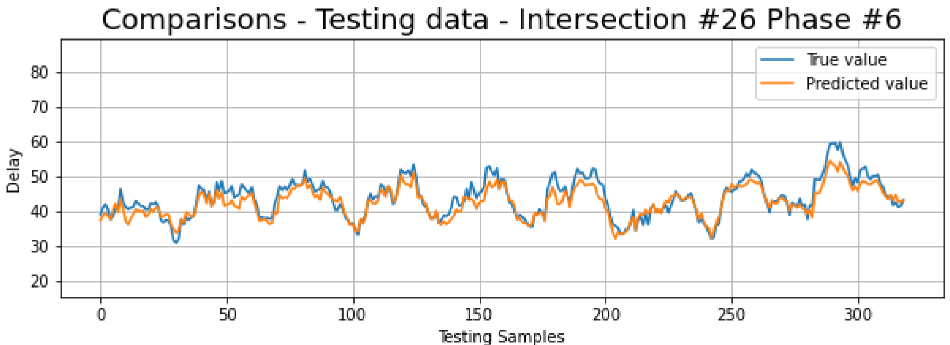
- **Testing:** Intersection 26





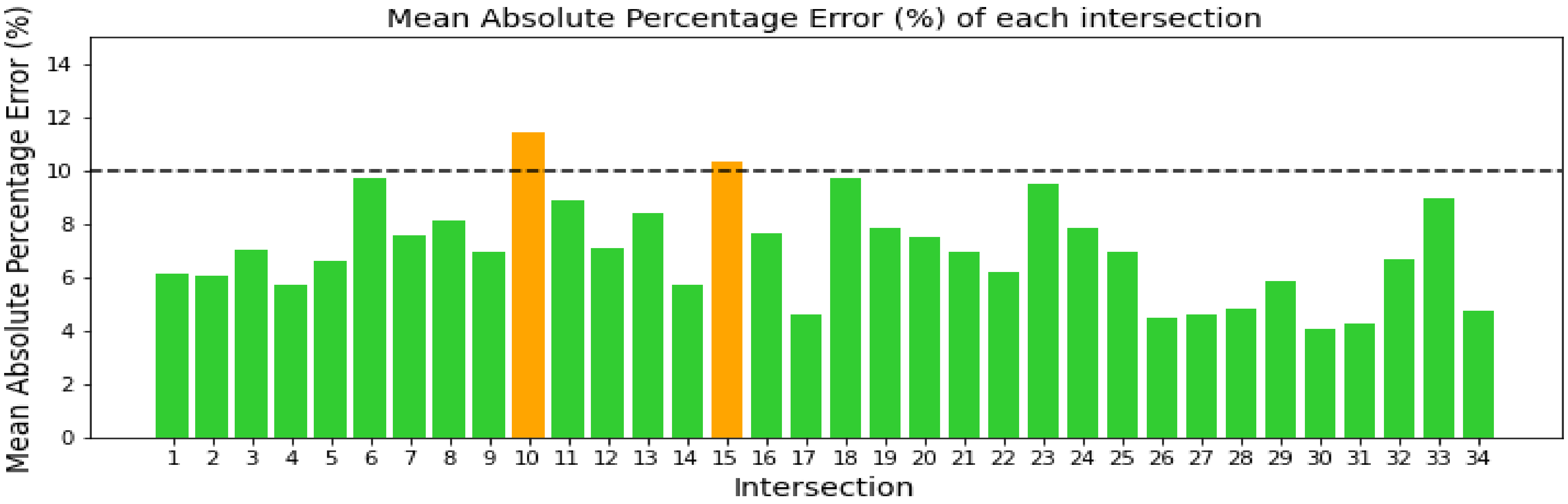


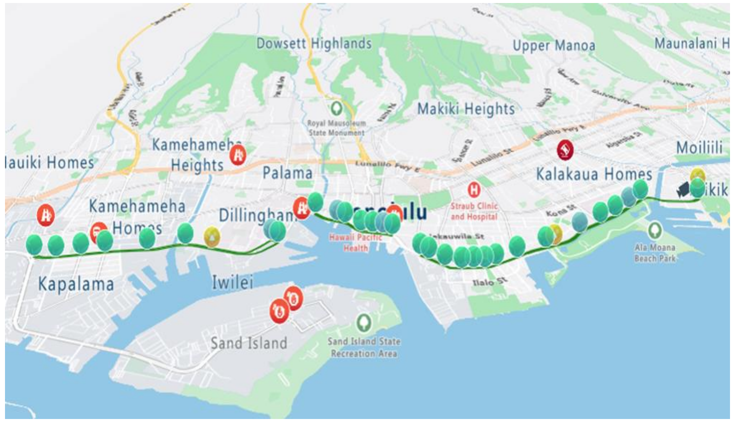




4.3 Modeling Summary (34 intersections)

As planned, now we have completed the neural network modeling for all the intersections with average error <10%
Milestone one completed on time.





$$CI = \frac{\sum_{i=1}^{N}(error_i < 0.1)}{N}$$

	Confidence Interval (CI)
Training	98.24%
Testing	94.50%

4.4 Signal Control Optimization

Problem to be solved

$$Minimize\ ||y(k+1)||^2$$

$$S.T: umin(k) \leq u(k) \leq umax(k)$$

$$y(k+1) = A\,y(k) + B_1 u_1(k) + B_2 (H_2)^{-1} (C - H_1 u_1(k)) + F(y(k), u(k-1), v(k); \pi)$$

Expanding the terms:

$$y(k+1) = A\,y(k) + (B_1 - B_2 (H_2)^{-1} H_1) u_1(k) + B_2 (H_2)^{-1} C + F(y(k), u(k-1), v(k); \pi)$$

Denote the following measurable NONLINEAR term,

$$G = A\,y(k) + B_2 (H_2)^{-1} C + F(y(k), u(k-1), v(k); \pi)$$

$$V = (B_1 - B_2 (H_2)^{-1} H_1)$$

Finally, we have

$$y(k+1) = G + V u_1(k)$$

4.5 Adaptive Signal Control in VISSIM – Coding Structure

Step 0: Estimate A, B and $\boldsymbol{\pi}$ (NN weights) matrices using VISSIM data.

Step 1: Simulate for (k) signal cycles (k=2).

Step 2: Update A, B and $\boldsymbol{\pi}$ matrices

$$A(k+1) = A(k) - LR * Gradient$$
$$B(k+1) = B(k) - LR * Gradient$$
$$\boldsymbol{\pi}(k+1) = \boldsymbol{\pi}(k) - LR * Gradient$$

Step 3: Optimize for optimal control $u(k)$ using the updated matrices $A(k+1)$, $B(k+1)$, and $\boldsymbol{\pi}(k+1)$.

Step 4: Update signal timing plan u(k) for the next available cycle and simulate for (k) signal cycles (k=2).

Step 5: Go to *step* 2.

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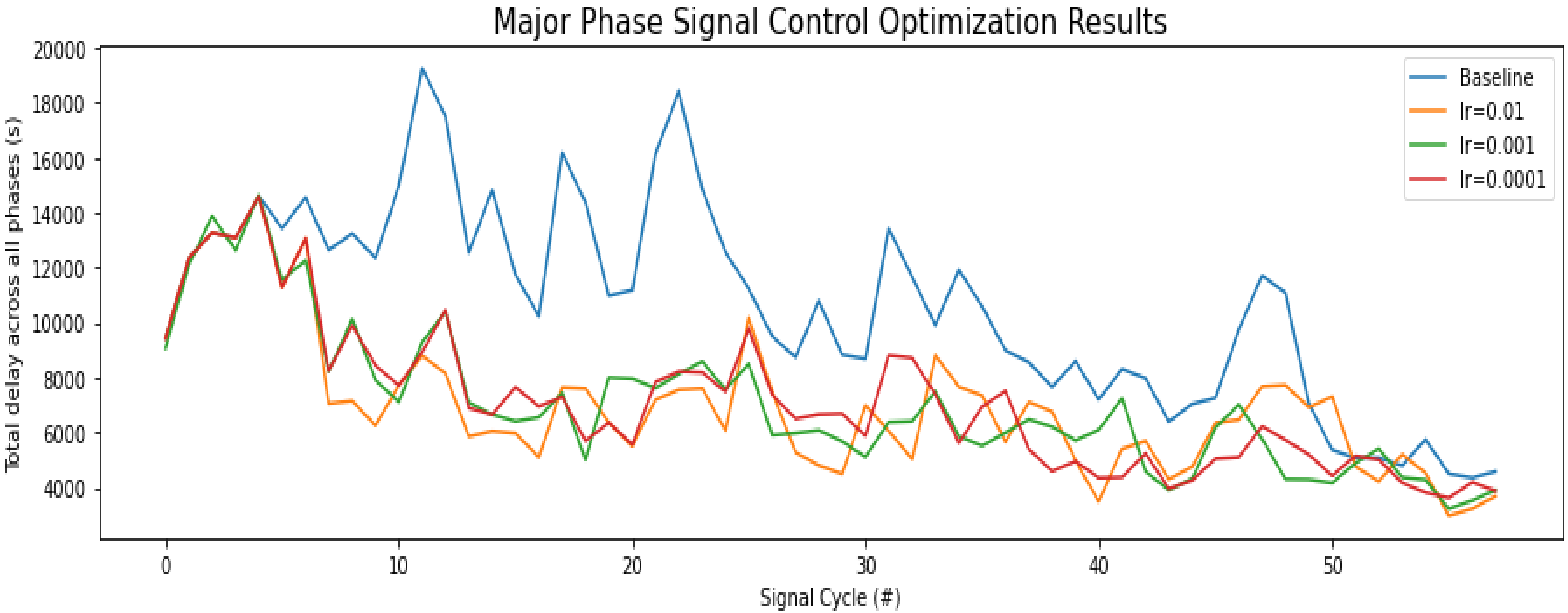
4.5 VISSIM Based Closed Loop Adaptive NN Control - Comparison between Baseline and 3 Different Simulations

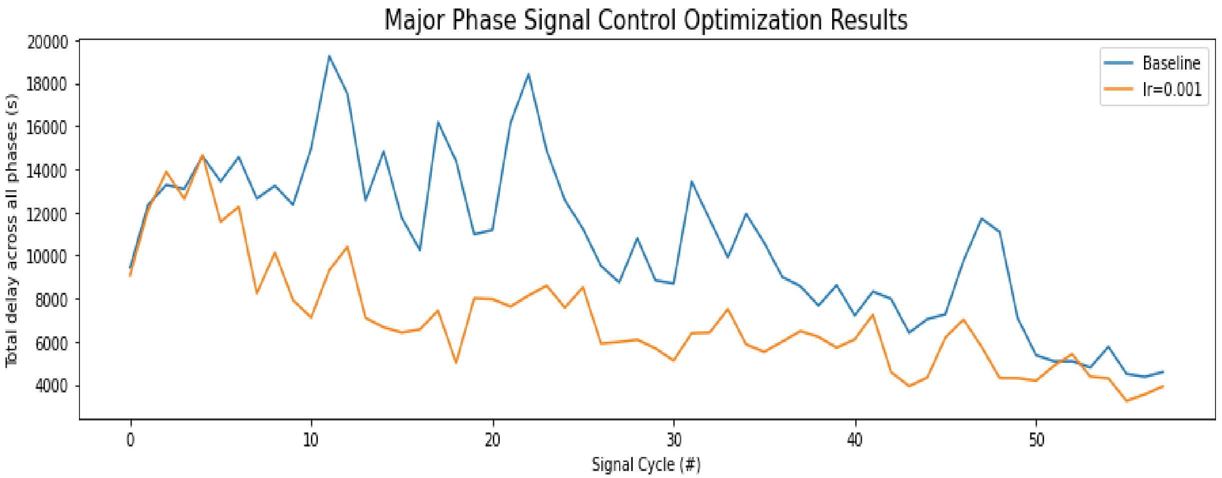


4.5 Closed Loop Adaptive Control Considering Queue Length

Conditions:

- LB for minor phases = 0 sec
- UB for minor phases = 10 sec
- LB for major left phases = 10 sec
- UB for major left phases = 20 sec
- LB for major phases = 120 sec
- UB for major phases = 180 sec
- Learning Rate = 0.001
- Vehicle Volume = 5504/hr

$$Weight\ for\ phase(i) = \frac{Volume\ at\ phase\ (i)}{Total\ Volume}$$



Total delay for phase = (delay per vehicle) x (number of vehicles)

Performance:

Mean improvement from baseline (Sum of delay across all phases) = 34.03% (lr = 0.001)

Mean improvement from baseline (Sum of delay across all phases) = 33.19% (lr = 0.0001)

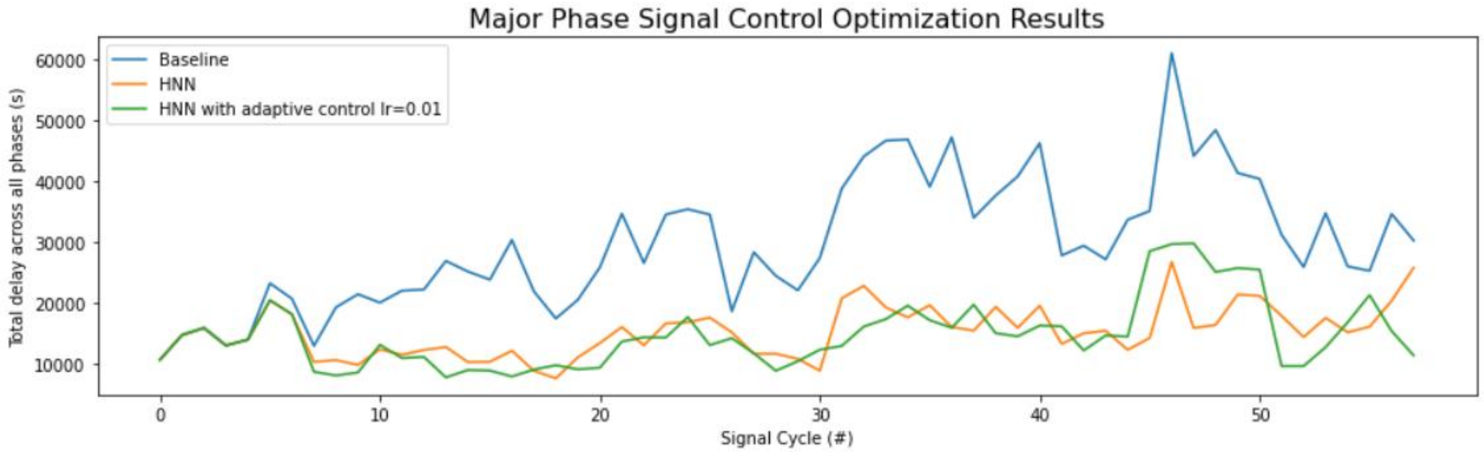
Mean improvement from baseline (Sum of delay across all phases) = 34.50% (lr = 0.01)

4.5 VISSIM Based Closed Loop Adaptive Control Considering Queue Length with 10% Increase in Vehicle Volume Every 5 Cycles

Conditions:

- LB for minor phases = 0 sec
- UB for minor phases = 10 sec
- LB for major left phases = 10 sec
- UB for major left phases = 20 sec
- LB for major phases = 120 sec
- UB for major phases = 180 sec
- Learning Rate = 0.01
- Vehicle volume = 1.1*5504 per hour/5 cycles

$$Weight\ for\ phase(i) = \frac{Volume\ at\ phase\ (i)}{Total\ Volume}$$



Total delay for phase = (delay per vehicle) x (number of vehicles)

Mean improvement from baseline (Sum of delay across all phases) = 48.89% (without adaptive control)

Mean improvement from baseline (Sum of delay across all phases) = 50.74% (with adaptive control)

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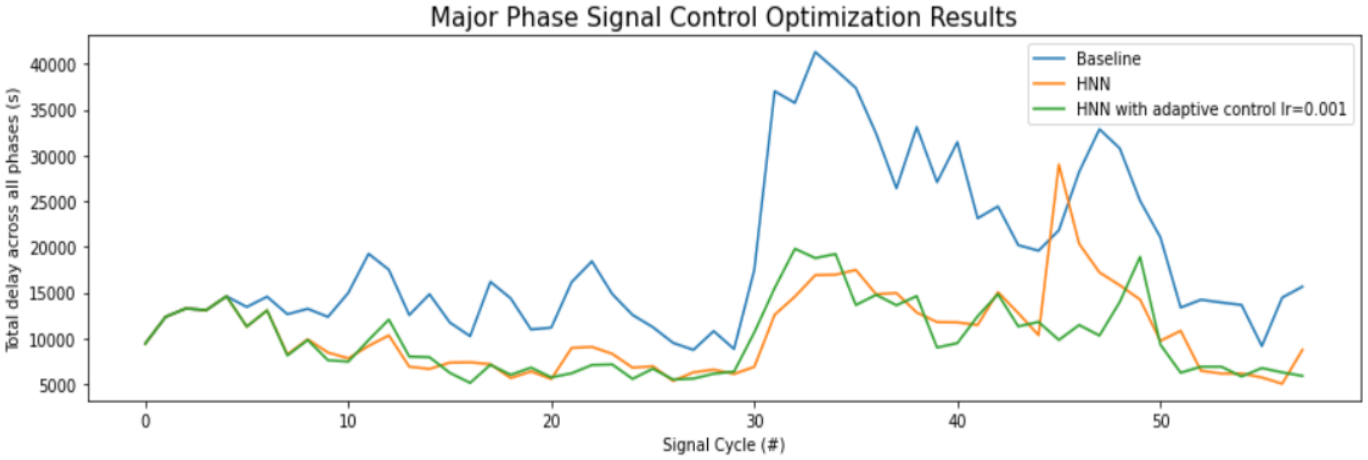
4.5 VISSIM Based Closed Loop Adaptive Control Considering Queue Length with 2x Vehicle Volume after 30 Cycles

Conditions:

- LB for minor phases = 0 sec
- UB for minor phases = 10 sec
- LB for major left phases = 10 sec
- UB for major left phases = 20 sec
- LB for major phases = 120 sec
- UB for major phases = 180 sec
- Learning Rate = 0.001
- Vehicle volume = 2*5504 per hour/30 cycles

$$Weight\ for\ phase(i) = \frac{Volume\ at\ phase\ (i)}{Total\ Volume}$$



Total delay for phase = (delay per vehicle) x (numbe

Mean improvement from baseline (Sum of delay across all phases) = 43.78% (without adaptive control)

Mean improvement from baseline (Sum of delay across all phases) = 47.05% (with adaptive control)

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4.6 Energy Modeling for the First Corridor (9 intersections)

Tasks completed:

- Used the data available (VISSIM trajectories data) to estimate the energy and formulate the energy calculation;
- Built up initial neural network models between the energy and the signal timing plans, the following have been considered:

  1) Inputs: Time plans *u(t)* for the period between the starting time t_0 and the ending time t_f of vehicles passing through the first corridor

  2) Output: Energy consumed at the end of corridor, i.e.,

$$E(t_f) = \sum_{i=1}^{N} \{ \int_{t_0}^{t_f} Power_i \left(u(t)\right) dt \}$$

Fuel consumption or number of stops would indicate energy $E(t_f)$.

Note: This is a batch inputs and single valued output modeling.

4.6 Energy Modeling - Mean and Variance Approach (Only Corridor 1#)

This requires us to use the follow data base to obtain the model for N = 30 (60 hours of run)

Signal time

Energy

Neural Network Modeling

Mean	Variance	Energy
$u_M(1) \in R^{43}$	$u_V(1) \in R^{43}$	$E(t_f, 1)$
$u_M(2)$	$u_V(2)$	$E(t_f, 2)$
$\cdots$	$\cdots$	$\cdots$
$u_M(N)$	$u_V(N)$	$E(t_f, N)$

This will allow us to build up the following model

$E\left(t_f, i\right) = f(u_M(i), u_V(i))$, NN size will be 86 inputs and 1 output

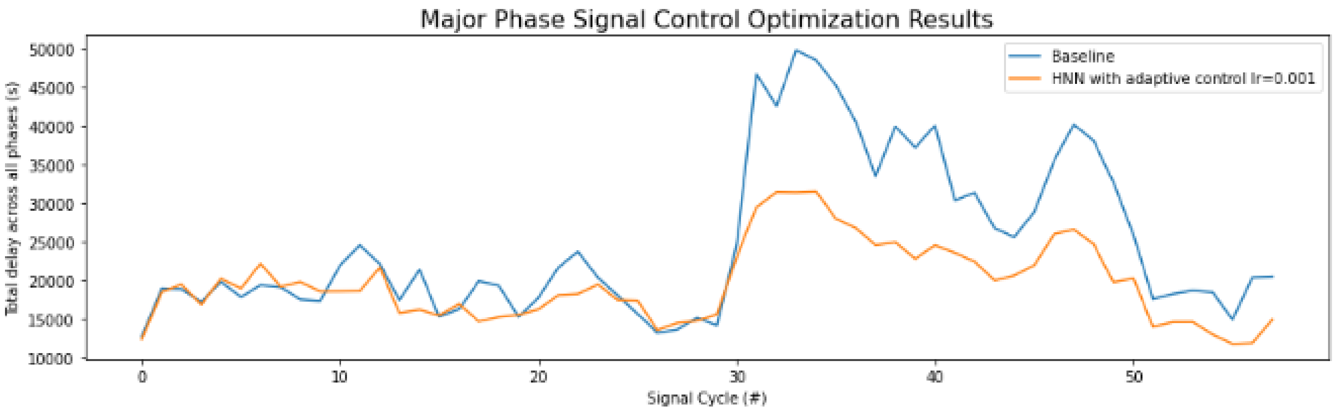
where $f(\ldots)$ is the unknown nonlinear function to be learned by neural networks

4.6 Summary of Results for 2X Volume Change after 30 Cycles

$$Fuel\_Consumption = \int_0^T \exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3} K_{ij}\,(3.6v_t)^i(3.6a_t)^j\right) dt$$

TABLE I
COEFFICIENTS FOR FUEL CONSUMPTION

K_{ij}	$a_n(t)$ is nonnegative				$a_n(t)$ is negative			
	j=0	j=1	j=2	j=3	j=0	j=1	j=2	j=3
i=0	-7.735	0.2295	-5.61E-3	9.773E-5	-7.735	-0.01799	-4.27E-3	1.8829E-4
i=1	0.02799	0.0068	-7.722E-4	8.38E-6	0.02804	7.72E-3	8.375E-4	3.387E-5
i=2	-2.228E-4	-4.402E-5	7.90E-7	8.17E-7	-2.199E-4	-5.219E-5	-7.44E-6	2.77E-7
i=3	1.09E-6	4.80E-7	-3.27E-8	-7.79E-9	1.08E-6	2.47E-7	4.87E-8	3.79E-10



Scenario Name	Direction	VT-Micro Fuel Economy (mpg)	Improvement (%)
Baseline	EB	18.81	-
Optimal Control	**EB**	**20.18**	**7.27%**
Baseline	WB	20.34	-
Optimal Control	**WB**	**22.22**	**9.22%**

Delay Improvement: 37%

5. Collaborations and Coordination with Other Institutions

The project team is composed of ORNL, University of Hawaii, Econolite Systems and Hawaii DOT, where **ORNL team lead the project and will work on AI-modeling, control design and leads 24/7 real-time implementation.**

The collaborative activities are as follows:

- **University of Hawaii** (Professor Guohui Zhang and Dr Arun Bala Subramaniyan)**:**
  - Data processing
  - Neural network modeling and VISSIM simulation
- **Econolite Systems** (Dr Jon Ringler and Nick Ullman)**:**
  - Data collection and processing
  - Real-time modeling and control interface
  - Probability density function shaping for modeling error
- **Hawaii DOT** (Edwin H Sniffen)**:**
  - Facilitates 24/7 implementation
  - Provides 10+ vehicles with onboard units to real-time testing

ORNL Team Members:

Dr Chieh (Ross) Wang
Dr Wan Li
Dr Yunli Shao
Dr Tim Laclair
Dr David Smith
Dr Jacky Rios-Torres
Dr Yaosuo Xue

6. Remaining Challenges and Barriers

Most studies on AI for intersectional signal control only consider a few intersections, and no real-time learning system has been deployed for large-scale field testing because of the lack of comprehensive real-time data and user-friendly interfaces to the implementation. These shortcomings have limited the current research on AI for mobility at the simulation level.

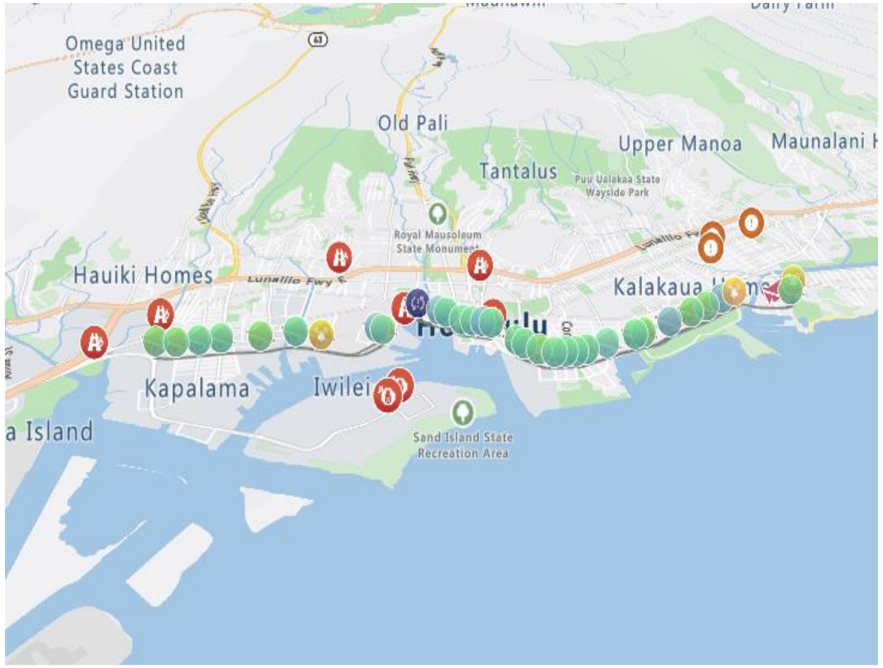
Moreover, energy efficiency has not been well addressed for these AI-based modeling and controls. This constitutes the following challenges and technical barriers:

- **Although the theory of AI-based modeling and control for signal control is maturing, the field testing and closed-loop control implementation for large number of intersections is still limited because of the insufficient real-time data for fast feedback control realization;**
- **The existing AI-based modeling for transportation systems cannot yet capture the nonlinear and dynamic stochastic nature with high reliability and robustness; and**
- **Guaranteed control performance for the energy minimization is still lacking.**

The project therefore focuses on the development and implementation of real-time learning and adaptation for the signal control along the arterial, where both NN modeling and control will be adaptively learned during the real-time system operations.

7. Planned Future Research

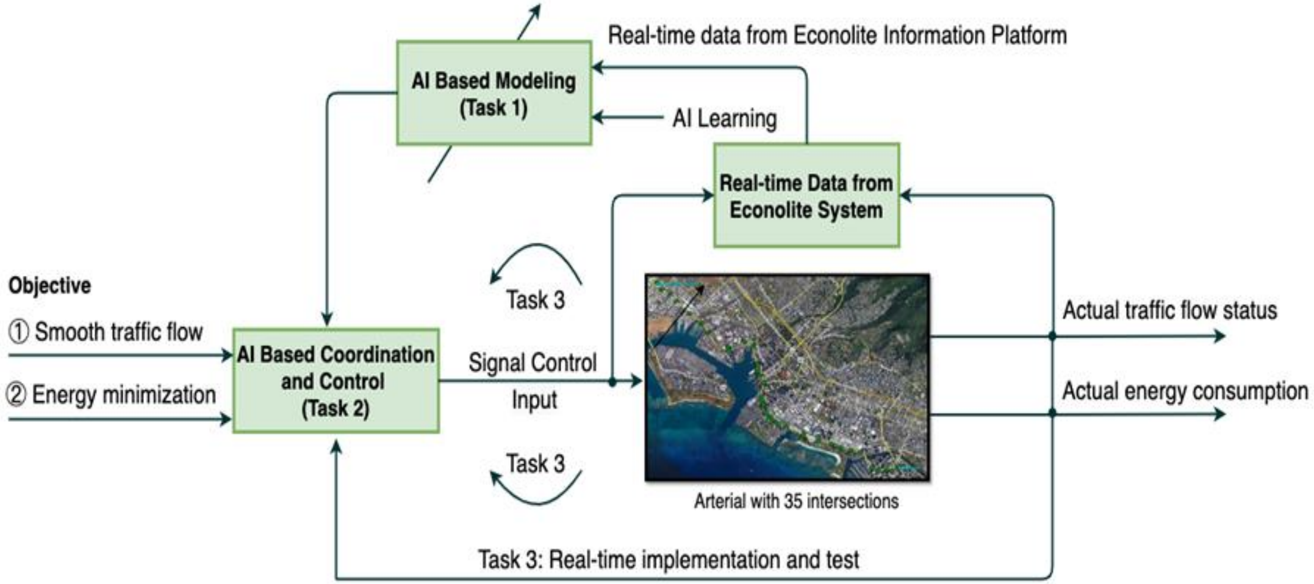
- **Further Data Processing**
  - Collect more data to train HNN
  - Include signal phases for both major and minor streets
  - Include more features, e.g., traffic volume.
- **Continued Neural Network Modeling**
  - Complete HNN modeling for all the 34 intersections
  - Use Different NN structures, e.g., RNN, LSTM.
  - Use different sample intervals, e.g., every 2-4 cycles
  - Explore probability density function shaping for modeling
  - Validate data processing output with ground truth videos
- **AI Controller Design (July 2022 – August 2022)**
- **Real-time implementation (September 2022 – Jan 2023)**



Any proposed future work is subject to change based on funding levels.

8. Summary

- **Accomplishments**
  - Completed AI-based modeling for all the 34 intersections along Nimitz Highway and Ala Moana Boulevard arterial with a <10% modeling error as expected with >95% confidence interval.
  - Completed optimal and adaptive controller design and preliminary VISSM testing with > 30% delay reduction and 10% fuel savings
  - Produced 5 publications and received 1 best paper award
- **Review Responses**
  - There was no review comments due to the late start of the project last year



Thank you for your attention